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Article

Modeling of Forest Fire Risk Areas of Amazonas Department, Peru: Comparative Evaluation of Three Machine Learning Methods

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Abstract: Forest fires are the result of poor land management and climate change. Depending on the type of the affected eco-system, they can cause significant biodiversity losses. This study was conducted in the Amazonas department in Peru. Binary data obtained from the MODIS satellite on the occurrence of fires between 2010 and 2022 were used to build the risk models. To avoid multicollinearity, 12 variables that trigger fires were selected (Pearson $\leq$ 0.90) and grouped into four factors: (i) topographic, (ii) social, (iii) climatic, and (iv) biological. The program Rstudio and three types of machine learning were applied: MaxENT, Support Vector Machine (SVM), and Random Forest (RF). The results show that the RF model has the highest accuracy (AUC = 0.91), followed by MaxENT (AUC = 0.87) and SVM (AUC = 0.84). In the fire risk map elaborated with the RF model, 38.8% of the Amazonas region possesses a very low risk of fire occurrence, and 21.8% represents very high-risk level zones. This research will allow decision-makers to improve forest management in the Amazon region and to prioritize prospective management strategies such as the installation of water reservoirs in areas with a very high-risk level zone. In addition, it can support awareness-raising actions among inhabitants in the areas at greatest risk so that they will be prepared to mitigate and control risk and generate solutions in the event of forest fires occurring under different scenarios.

Keywords: spatial modeling; probability; remote sensing; forest risk; random forest

1. Introduction

Forest fires are unforeseen events attributed to climate change [1], in addition to being considered the main threat to ecosystems and human life [2]. However, another cause of these events is related to human activities [3]; from 1992 to 1912 in the United States (during which 1.5 million wildfires had to be extinguished or managed by state or federal agencies), humans greatly expanded the spatial and seasonal "niche" of fire, accounting for 84% of all reported wildfires and 44% of the area burned [4]. These fires cause negative impacts on natural resources and alter ecosystem function and landscape succession [5,6]. Globally, they are considered an adverse event since their main consequences include loss of biodiversity, deterioration of soil quality [7], environmental pollution with the emission of gases into the atmosphere [8], and significant losses of forested areas [9]. Unfortunately, the impact of individual factors on forest fires varies, depending on the geographical region and its natural and socio-economic condition [10].

According to the World Wildlife Fund, every year, 200,000 forest fires occur worldwide, and the burned area represents more than 1% of the world's total forest area [11,12]. While these figures are already impressive, they are likely to worsen in the future [13]. Peru has more than 72 million ha (56.09%) of its territory covered by forests, which are home to a great diversity of flora and fauna and provide a diversity of resources and ecosystem services. This scale positions Peru as the country with the second-largest area of natural forests in South America [14]. Fires adversely affect flora and fauna [15], so the effects of fires can be devastating for the country. However, in the last two decades, forest fires have severely impacted several regions of Peru, such as Cajamarca, Cusco, Apurímac, and Puno, among others [16]. In the Peruvian Andes between 2018 and 2019, approximately 10,000 forest fires affected 367,000 ha of vegetation cover [17]

Wildfires are an accelerating problem, and both the media and scientific studies show that the incidence, severity, and losses are increasing [18]. Reports on forest fires indicate that between 2003 and 2012, the annual loss of forest because of fires was about 67 million ha, constituting about 1.7% of the world's forest areas [19]. In 2015, 98 million ha of forest area burned in tropical regions. Moreover, studies showed that fire dynamics are changing worldwide due to climate change and land use [20]. For this reason, the length and extent of the fire season are expected to increase significantly by the year 2100, placing forests under an increasing threat of high-severity fires [21].

Climate change has made wildfires larger, more intense, and more common [22]; it is therefore important to analyze these risks, as the likelihood of heat and drought will increase due to the impacts of climate change [23]. The risk of forest fires is the result of constant and variable factors that are associated with the fire behavior triangle elements that influence their onset, spread, and difficulty of fire control [24], constantly threatening the community's ecological system, infrastructure, and environmental aspects.

Risk assessment can use probability to express the uncertainty of the occurrence or intensity of hazardous events [25]. There is an urgent need to carry out such studies [26] and map the forest areas facing the risk of fires [27]. Geographic information systems (GIS) and remote sensing (RS) techniques are well-known for their effectiveness in modeling areas of forest fire occurrence [28]. Moreover, these techniques can be used to develop reliable prediction models of fire risk areas, ensuring public safety, forest management, and fire suppression planning [29].

Remote sensing is one of the few tools available to systematically monitor forest recovery over large areas of land [30]. The remote sensing approach for the detection of burned areas in active and post-fire areas is now well recognized by the scientific community [30–32]. satellite remote sensing can acquire images of various resolutions over large areas, allowing rapid assessment of fire situations and facilitating the analysis of fire development and spread trends, as well as the accurate identification of burned areas [33]. Despite the development of different remote fire detection products, the demands of fire managers are not always met due to the different spatial and temporal resolutions of the sensors [34].

To address the aforementioned limitations, remote sensing-based wildfire risk assessment methods can be classified into three types: (a) mathematical and statistical methods, (b) forest fire danger indices, and (c) machine learning models [35]. Machine learning (ML) models can integrate many factors to predict fire occurrence and spread with a high degree of accuracy. In addition, they facilitate the simulation of future scenarios by incorporating different land use changes and climate change projections [36,37] and allow for predicting the behavior, spread, and risk of forest fires [6,38,39], obtaining reliable results due to their high prediction performance [40]. The most widely used ML algorithms for predicting forest fire risk areas are Random Forest (RF) [41,42], Support Vector Machines (SVM) [43–45], and MaxEnt [46–48]. In all cases, the authors concluded that ML algorithms show promising results in predicting forest areas at risk of fires. However, it is necessary to compare the abovementioned methods to obtain reasonable conclusions for specific regions.

The prediction of areas susceptible to the occurrence of forest fires considers different variables of different categories; some of them can be quantitative, and others qualitative [19,49], which makes it difficult to integrate them in a spatial model. In view of this, machine learning algorithms can handle non-linear and highly dimensional data and thus solve the problem of integrating variables to achieve the objective [1,50]. ML models, a subset of artificial intelligence, have become involved in fire monitoring and fire severity assessment; they analyze historical data to create predictive models capable of forecasting the spread of future fires [51]. There are studies around the world where machine learning algorithms are used for forest fire risk prediction, such as those conducted in Indonesia [52–54], Brazil [36,55,56], and other countries.

Several papers compared different statistical and machine learning (ML) techniques to generate fire occurrence susceptibility maps [57–59], demonstrating the ability of the machine learning approach to identify areas that could be affected by wildfires in the near future. Thus, Moghim and Mehrabi [60] used ML to predict wildfires using historical data and influential variables. They evaluated the performance of two machine learning algorithms, logistic regression (LR) and random forest (RF), to construct wildfire susceptibility maps in regions with different physical characteristics. In general, the RF model outperformed the LR model in almost all cases. Ref. [61] used random forest (RF) to identify areas that could be affected by wildfires in the near future. The results demonstrated the ability of the RF approach to identify areas that could be affected by wildfires in the near future, as well as its effectiveness in evaluating the effectiveness of fire suppression activities.

In Peru, information on the effects of forest fires is scarce. In addition, there is limited research on long-term fire prediction that integrates environmental, meteorological and human factors, particularly at broader geographic scales [62], so the proposed approach uses the high efficiency of machine learning algorithms to combine data from various sources, being crucial to map the dynamics and evolution of fire regimes over time.

In Peru, forest fires have increased in recent years, generating problems of environmental pollution, ecological imbalance, and economic and human losses [63]. Despite the fact that forest fires occur more rapidly in this country, studies on the probability of occurrence of forest fires are still limited. Some of the studies used fuzzy logic and GIS to map the susceptibility to forest fires in a watershed in the Cajamarca region [24]. One another study conducted in Junín used geographic information systems to map the risk potential of forest fires [63], while another study modelled forest fire risk zones in the high Andean areas of Peru [64]. However, none of these studies used ML algorithms.

The Amazonas region has experienced a large number of forest fires that have devastated large areas of forest plantations and natural forests. From 2017 to 2019, 162.24 km^2 was burned, negatively impacting the Yungas ecosystems (basimontane forest, montane forest, and ultramontane forest) and Jalca, with the fires distributed in the provinces of Utcubamba, Luya, and Chachapoyas [65], and this has been detrimental to the local economy, wildlife, and archaeological monuments of high cultural value, such as the Kuelap Fortress, which has been affected by the forest fires that occur on the periphery of this historical center, as on some occasions the fire damaged the natural vegetation that protects it. However, there are no specialized studies where the prediction of areas with the highest risk of this event occurring was carried out. Therefore, this research was carried out to model the risk of occurrence of forest fires, taking the Amazon region of Peru as a case study, using machine learning algorithms (RF, SVM and MaxEnt), evaluating their performance and generating a reliable report on the use of these algorithms in the forest fire risk context. In addition, forest fire risk mapping will serve as a crucial tool in forest fire prevention measures and will help in the identification of high-risk areas prone to such occurrences. Furthermore, decision makers will have the necessary information to implement fire prevention measures, such as fire risk zoning and fuel management to reduce fire losses [25,66,67].

2. Materials and Methods

2.1. Study Area

The study was conducted in the department of Amazonas, located in northeastern Peru in South America; this department is located between latitudes 3°0′ S and 7°2′ S and longitudes 77°0′ W and 78°42′ W. Amazonas presents a remarkable altitudinal variation, ranging from 169 m above sea level in the lowest parts to 4242 m above sea level in the highest parts (Figure 1), and its topography is quite rugged with a large number of mountains, which causes the climatic variation to be very marked. In the lowest areas, maximum temperatures reach 40 °C, while in the highest areas, minimum temperatures can drop to 2 °C. Annual rainfall varies significantly, with deficits of up to 924 mm in some areas and surpluses exceeding 3000 mm in others [68]. Amazonas has a great ecosystemic wealth due to its geographical location and its climatic and topographic qualities. This department has ecosystems such as Jalca, seasonally dry forests, montane forests, and lowland rainforests, which are home to a large number of endemic fauna and flora, such as gallito de las rocas (*Rupicula peruvianus*), oso de anteojos (*Tremarctos ornatos*), colibri cola de espátula (*Loddigesia mirabilis*), and timber trees with great economic and ecosystemic value, such as *Cedrela* sp., *Ceiba* sp., and *Cedrelinga cateniformis*, among others. In the department of Amazonas, the Amazonian Andes and grasslands cover 13.9% of the territory, and seasonally dry and humid forests represent 86.1% of the surface. The soils are varied, influenced by climate, relief, geological structure, vegetation, and human intervention, reflecting the complexity and ecological richness of this territory.

2.2. Forest Fire Data

The database consisted of a binary set of fire (code 1) and non-fire (code 0) points [49,69–71]. The fire points were obtained from the Moderate Resolution Imaging Spectroradiometer (MODIS) data on board the AQUA_M-T satellite available in the Queimadas database on the website of the Instituto Nacional de Pesquisas Espaciais (INPE) (https://terrabrasilis.dpi.inpe.br/queimadas/bdqueimadas/, accessed on 15 February 2023). This database provides information such as coordinates and fire risk identified by the satellite [72]. In this study, the area of the department of Amazonas was filtered for the period 2010 to 2022, resulting in a total of 1670 fire data points from which the geographic coordinates were extracted and subsequently transformed to a point-type shapefile in Qgis (v 3.36.3) and represented the fire data (code 1). Each fire point indicates the occurrence of fire in a pixel that changes size by the spatial resolution of the satellite. The AQUA_M-T satellite has a spatial resolution of 1 km and can detect fire fronts of at least 30 m long and 1 m wide; therefore, the same pixel could have one or several fire fronts, generating a single active fire focus when in reality there is more than one fire front and vice versa [73]. Although the AQUA_M-T satellite only detects a fraction of all fire events, due to methodological standardizations, it provides the most suitable data to investigate spatial and temporal trends in fire occurrence [74]. The non-fire points (code 0) were generated from a random sample of points from locations in areas where no fires were recorded by INPE's AQUA_M-T satellite, using the random points within the polygons tool of the GIS software Qgis (v 3.36.3). In this case, the polygon of the department of Amazonas, which is the study area, was used.

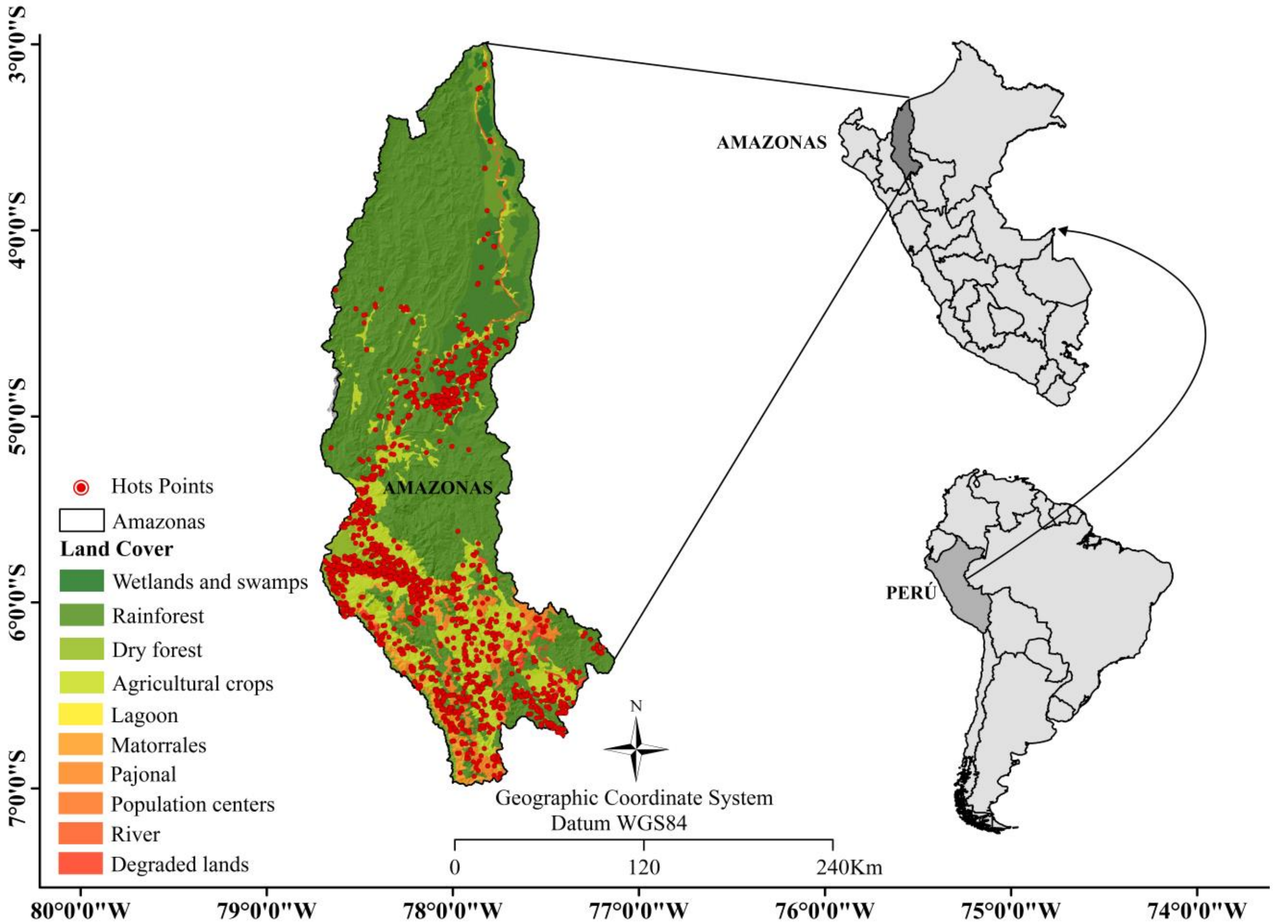

Figure 1. Location of the Amazonas department, Perú.

2.3. Factors Related to Forest Fires

In this study, the factors influencing forest fire were divided into four categories: topographic factors, social factors, climatic factors, and biological factors [75]. In total, 14 predictor variables were selected based on an extensive literature review of wildfire risk and considered variables pertaining to meteorological, social, biological, and topographical factors (Table 1) [8,44,76–78], as these factors were identified as having a direct or indirect influence, either positive or negative, on the occurrence of forest fires, and they were determinants for the initiation, spread, and duration of forest fires, crucial aspects for the determination of risk levels in the study area. The variables were generated and processed in QGIS (v. 3.36.3) software, where they were cropped according to the extent of the study area with the extraction tool and resampled to 90 m with the resample tool of the QGIS bilinear algorithm. This algorithm is commonly used in image and geospatial data processing, as it is a relatively simple method with good image quality [79] and presents advantages over other traditional interpolation methods such as bicubic and nearest neighbor due to its ability to balance the quality of the results, as it has no pixel scaling and no impact on the parameters being evaluated [78], results in a finer and smoother image [80], and has good computational efficiency because it is less complex, using only four neighboring pixels [81]. This resolution (90 m) is optimal for balancing information with data processing efficiency, avoiding the computational complexity and high processing times usually associated with finer resolutions (Figure 2) [82].

Table 1. Variables used.

Factor	Variables	Description
Topographic	Elevation Aspect Slope TWI	Elevation (masl) Aspect Slope (°) Topographic Humidity Index
Social	Distance to roads Distance to rivers Distance to population centers	Distance to roads (m) Distance to rivers (m) Distance to population centers (m)
Climatic	Temperature Humidity (*) Radiation (*) Rainfall Wind speed	Temperature (°C) Humidity (Kpa) Radiation (nm) Rainfall (mm) Wind speed (km/h)
Biological	Normalized Difference Vegetation Index Land Cover	NDVI LC

Note: (*) variables excluded with Pearson correlation $\geq$ 0.90.

The variables (Table 1) were analyzed with the Pearson correlation method using the corrplot package of R-4.2.3, where variables with a correlation coefficient $\geq$0.90 (*) were excluded from the models to avoid severe multicollinearity and improve the model's performance [67,83]. This process was realized because the multicollinearity affects all algorithms selected for this study, and in the case of Random Forest, it mainly influences the identification of the more important variables. Although RF copes well with variable redundancy [84], identifying multicollinearity makes it possible to verify which of the variables are really important. With respect to Maxent and SVM, it is also necessary to analyze multicollinearity [85], as both algorithms seek to identify the relevance between variables and to obtain models with clear, efficient results that are related to reality [19,86]. In this study, the Pearson analysis ensured the quality and robustness of the model, avoiding overfitting, reducing the predictive capacity, and increasing the certainty in the results [83] of the models of forest fire risk, thus resulting in 12 variables selected for the model.

Solar radiation and humidity were eliminated, resulting in variables with the highest correlation value ($\geq$0.90) in order to obtain better performance of the model without falling into the error of over-prediction. Assuming that removing radiation and humidity could affect the risk areas, this was compensated by the other climatic variables that were integrated, such as precipitation and temperature, which are very decisive for the risk of forest fires.

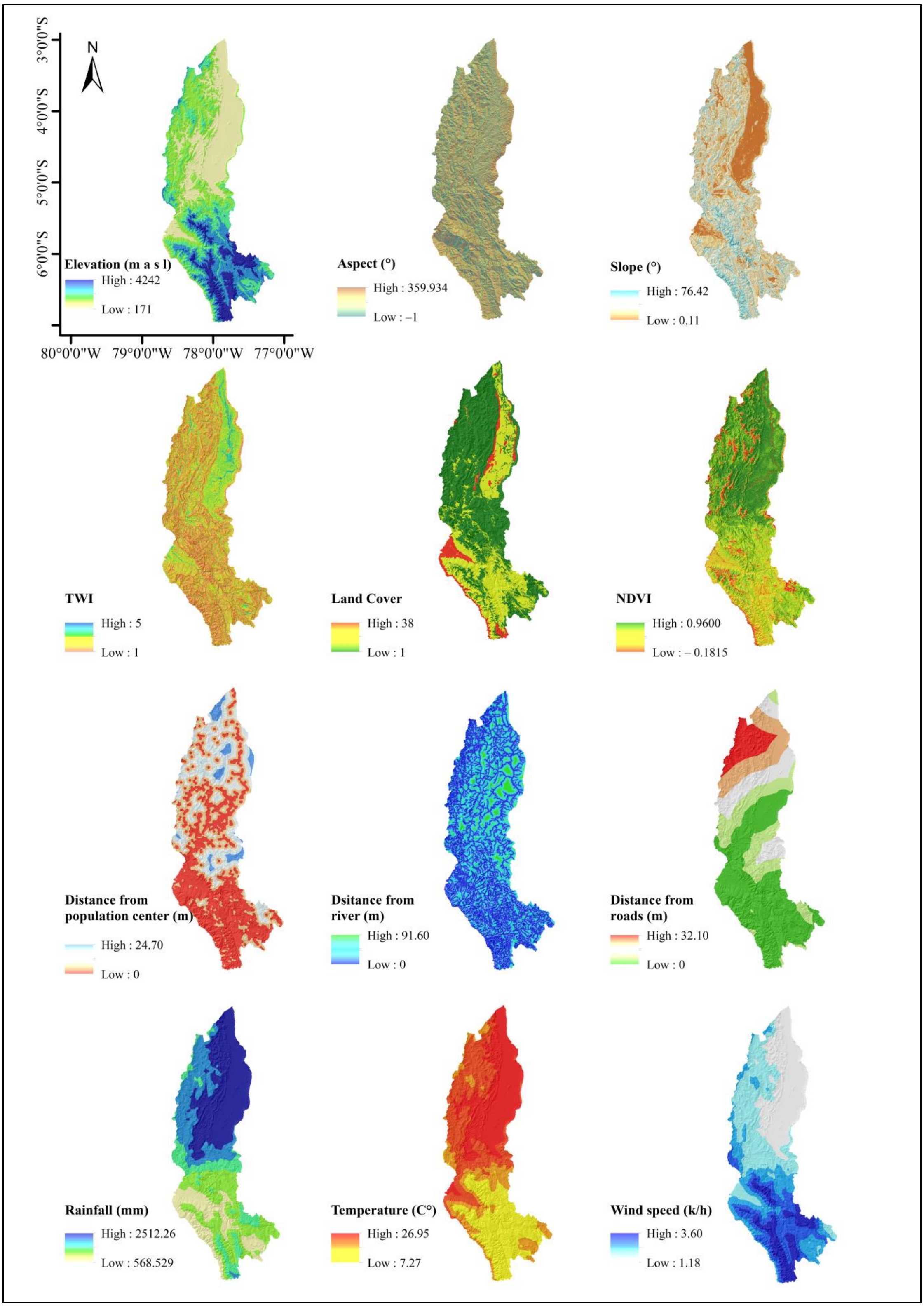

Figure 2. Variables used in the modeling.

2.3.1. Topographic Factors

From a Digital Elevation Model (DEM) [36,37] of the ASTER sensor obtained from the Alaska Satellite Facility Platform (https://search.asf.alaska.edu/, accessed on 15 February 2023), the ASTER DEM product was selected for this research because it provides data at a regional level that is beneficial for our study area, is freely available, has a spatial resolution of 30 m, and has a vertical accuracy of ±10 to ±25 [87] and provides better morphometric, geomorphological, and geological details [88,89]. The DEM was processed in QGIS (v 3.36.3) software, where the topographic factor variables (elevation, aspect, slope, and Topographic Wetness Index (TWI)) [38,39] were generated with the Raster Terrain Analysis tool. Elevation influences temperature, relative humidity, air temperature, precipitation, and heat conditions at the Earth's surface [90]. The aspect of a terrain influences its exposure to the sun, which in turn affects soil moisture, the condition of forest fuels, and wind patterns [91]. The slope of the terrain determines in the speed of fire spread; as slopes become steep, the speed of fire spread increases significantly [92]. TWI is an indicator that measures the long-term availability of soil moisture; with a lower value of TWI, it is assumed that the probability of wildfire will be higher in dry soil conditions [41,93,94].

2.3.2. Social Factors

The variables considered in the social factors were distance to roads, rivers, and population centers [95,96]. The Ministerio de Transporte y Comunicaciones Platform (https://portal.mtc.gob.pe/estadisticas/descarga.html, accessed on 16 February 2023) provided the road database. River data were obtained from the Autoridad Nacional del Agua platform (https://www.geoidep.gob.pe/autoridad-nacional-del-agua-ana, accessed on). Details about the population centers were extracted from the Instituto Nacional de Estadística e Informática (INEI) platform (http://sige.inei.gob.pe/test/atlas/, accessed on 16 February 2023). These variables were generated from the Euclidean distance in the QGIS (v 3.36.3) software with the r.grow.distance tool; the Euclidian distance is used to measure the proximity between geographic points [91,97].

2.3.3. Climate Factors

Climate factors include the variables of temperature, rainfall, and wind [92,98], essentials for forecasting flammability and fire behavior in different areas [8] obtained from the Worlclim Platform (https://www.worldclim.org/data/index.html, accessed on 16 February 2023). Temperature regulates vegetation desiccation, while precipitation reduces the probability of ignition [99], and wind speed is a determining factor in the spread of fire [86,100].

2.3.4. Biological Factors

Two variables were considered for the biological factors (normalized difference vegetation index (NDVI) and land cover) [101]. The NDVI was obtained using Landsat 8 satellite images [101,102], and land cover classification was obtained from the Ministerio del Ambiente, which included the following categories: forest (F), scrubland (S), paramo (P), shrubland (SH), agriculture (A), grassland (G), bare ground (BG), urban area (U), rivers (R), lagoons (L), and wetlands (W) [103,104].

2.4. Machine Learning Models

Several studies show that machine learning methods (e.g., artificial neural network (ANN), SVM, RF) outperform statistical techniques (e.g., discriminant analysis, logistic regression). These machine learning algorithms exhibit great potential for identifying and modeling complex nonlinear relationships between occurrences and evidential features [105–108]. Significant methods like Random Forest (RF), support vector machine (SVM), and maximum entropy (Maxent) have been successfully used to determine and predict forest fire occurrence in various parts of the world [8,109].

The three types of machine learning algorithms were MaxENT, support vector machine (SVM), and random forest (RF); these models are used in different parts of the world for forest fire risk spatial modeling [19,55,83], but comparisons of their precision are still scarce.

The MaxEnt model is frequently used to predict geographic distributions from observations of species occurrence through explanatory environmental variables [110]. Applied to wildfire modeling, it can work with occurrence data, without the need for a random point cloud as an absence background [111]. MaxEnt can use fire occurrence data, in addition to environmental parameters such as temperature and precipitation, to predict the potential distribution of a species or fire [110].

RF is an ensemble learning technique for classification, regression, and other tasks. It works by constructing a series of decision trees, where each tree is generated by bootstrapping samples and generates as output the mode of the classes (classification) or the average prediction (regression) of the individual trees [49,55]. On the other hand, in SVM, data points are represented in an n-dimensional space where they can be used to predict whether a new training example falls in the same category or in a different category. The main goal of SVM is to find a hyperplane in the n-dimensional space that can classify the data points [109,112,113].

In this sense, in this study, these models were processed using the R programming language through the RStudio interface (v. 4.3.3). The fire log data were divided into two groups corresponding to 70% training and 30% validation [44,114].

2.4.1. MaxENT

For the modeling process, the "DISMO" and "Java" packages were used (https://cran.r-project.org/, accessed on 17 February 2023). The model was configurated with 25 training repetitions, the regularization multiplier was set to 1, and a maximum number of 2000 pseudoabsences was chosen as representative of the reference database [28,115,116].

2.4.2. Support Vector Machine (SVM)

This machine learning method applies classification and regression based on maximization [6,112]. The algorithm is recognized for its versatility and effectiveness in solving a wide range of classification and regression tasks and is widely used for forest fire modeling in different countries worldwide [113].

2.4.3. Random Forest (RF)

Random Forest is a machine learning model that creates multiple decision trees to generate more stable and accurate predictions. To obtain the forest fire risk index values for the study area, the hyperparameters of the RF model were optimized, and it was determined that the parameter configuration with the best prediction accuracy was with 400 decision trees (ntree) and four random predictor variables (mtry) [6,117,118].

2.5. Validation of the Models

The AUC-ROC (Area Under the Receiver Operating Characteristic Curve) was used as the main validation metric for machine learning models, as it has the ability to evaluate the discriminative performance of predictive models using data such as presence and absence (fire and no fire) [119]. This metric allows models to be compared objectively and statistically, as it integrates sensitivity and specificity, providing a reliable evaluation even under conditions of high complexity and data imbalance [97,120,121]. This metric varies between 0 and 1, where a value of less than 0.5 indicates random classification performance, 0.5–0.7 indicates poor performance, 0.7–0.9 reflects moderate and acceptable performance, and an AUC greater than 0.9 shows high model performance [122–124]. In addition, the accuracy and F1 score were utilized as evaluation metrics; the accuracy measures the proportion of correctly predicted outcomes among all observations, providing an overall assessment of the model's predictive performance [125,126], and the F1 score, derived from the harmonic mean of precision and recall, provides a balanced evaluation metric suitable for unbalanced data [127].

$$AUC = \sum_{i=1}^{n-1} \frac{(X_i + 1 - X_i) * (Y_i + 1 + Y_i)}{2}$$

where $X_i + 1 - X_i$ is false positive rate of two consecutive points; $Y_i + 1 + Y_i$ is the corresponding true positive rate.

$$F1 - score = \frac{2 * precision * recall}{precision + recall}$$

where precision is the number of fires correctly detected among the total number of fires detected by the model; recall represents the number of fires correctly detected by the model among the actual number of fires; and the F1 score represents the harmonic mean between precision and recall [126,128].

The methodological process developed in this research can be seen in the methodological flowchart (Figure 3). The flowchart shows the methodological process, comprising four (04) steps: (1) selection of predictor variables classified into four types (topographic, climatic, social, and biological factors) and prioritization of variables through correlation calculations (r $\leq$ 0.9); (2) construction of a set of samples (hot points); (3) wildfire susceptibility modeling approaches based on three ML models (RF, SVM, MaxEnt); and (4) model evaluation and generation of fire risk maps based on the optimal model.

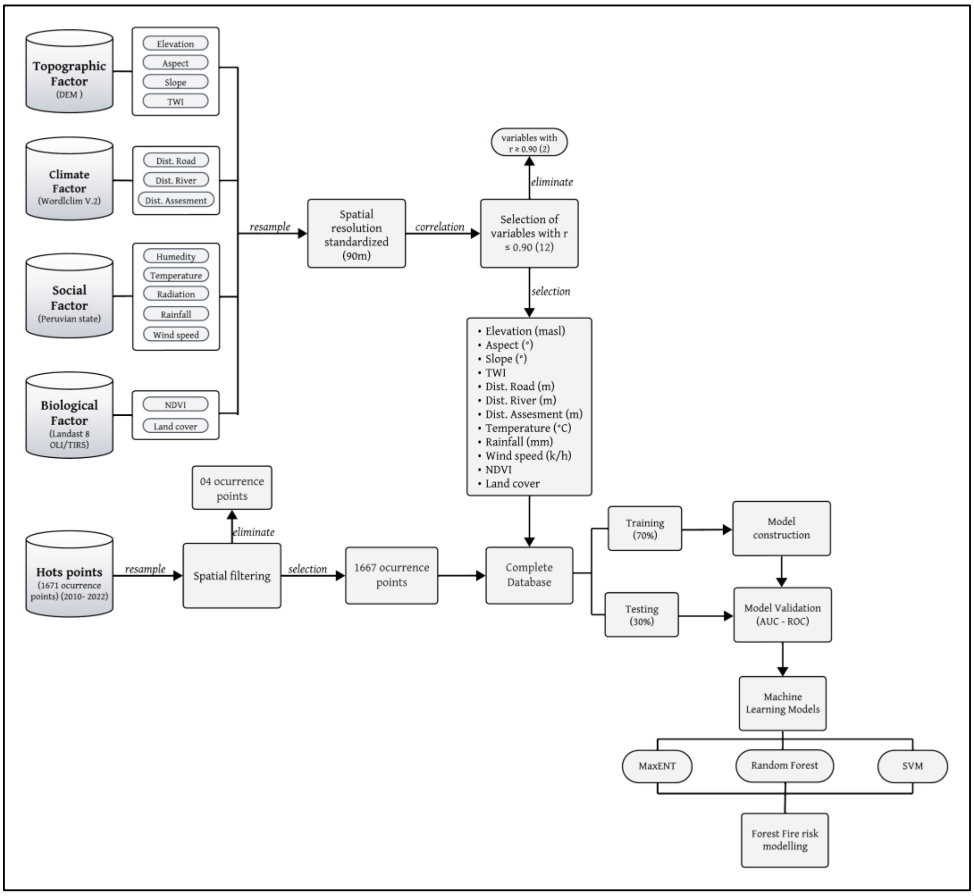

Figure 3. Flowchart methodology.

3. Results

3.1. Statistical Metrics of Machine Learning Models

The accuracy of the machine learning models had significant accuracy performance (Table 2), because the AUC values were between 0.84 and 0.91, Accuracy values were between 0.8513 and 0.8756, F1-score values were between 0.9054 and 0.9285, Recall values were between 0.8774 and 0.9624, and Precision values were between 0.9560 and 0.9860. The Random Forest model presented the highest performance of the three models and showed an AUC of 0.91 (Figure 4), where the blue and green lines indicate how accurate the model was in both the training (blue line) and validation (green line) phases and the red line indicates a random classifier. Table 2 presents the results of additional statistical metrics to validate the performance of the models used, where it can be seen that the MaxEnt model had the worst results, with Accuracy of 0.8513, F1 score of 0.9054, and AUC of 0.84. On the other hand, the Random Forest model presented more uniform results, with an AUC of 0.91, Accuracy of 0.8694, and F1 score of 0.9176.

Table 2. Statistical metrics of the machine learning models.

Statistical Metrics	Precision	Recall	F1 Score	Accuracy	AUC
Support vector machine	0.9860	0.8774	0.9285	0.8756	0.87
Random Forest	0.9560	0.8821	0.9176	0.8694	0.91
MaxEnt	0.9530	0.9624	0.9054	0.8513	0.84

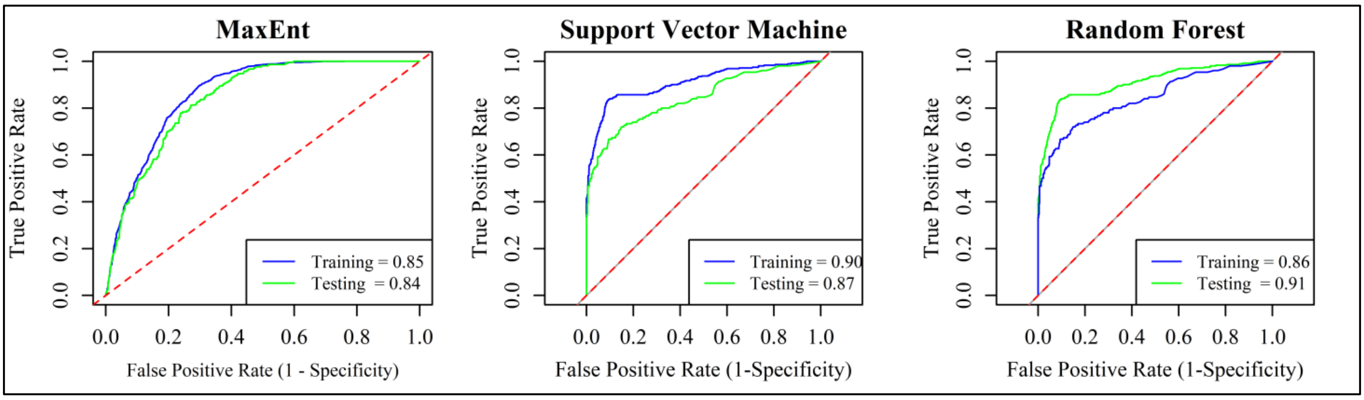

Figure 4. Area under the receiver operating characteristic curve (AUC-ROC) of the three machine learning models.

Table 3 presents the paired *t*-test results for the machine learning models used in this study, where it can be seen that all models presented *p*-value < 0.05 (2.20×10^{-16}), indicating that there was a significant difference between the results generated by each model used.

Table 3. Paired *t*-test of the machine learning models.

Comparation	Mean Difference	*t*-Value	*p*-Value	Confidence Interval
MaxEnt-SVM	−0.6999	−475.6555	2.20×10^{-16}	−0.703 to −0.697
MaxEnt-RF	−0.8620	−626.7131	2.20×10^{-16}	−0.865 to −0.859
RF-SVM	0.1621	472.8477	2.20×10^{-16}	0.161–0.163

Table 4 shows the 95% confidence intervals of each ROC (AUC) analysis result, where it can be seen that the Random Forest model that had an AUC value equal to 0.91, with an upper limit of 0.9218 and a lower limit of 0.8762, indicating that these results are more accurate and reliable compared to the MaxEnt and SVM algorithms.

Table 4. AUC confidence intervals.

Parameters		Minimum Value (CI 95%)	AUC Value	Maximum Value (95% CI)
Maxent	Training	0.8491	0.85	0.8827
SVM		0.8955	0.90	0.9341
RF		0.8219	0.86	0.8987
Maxent	Testing	0.8386	0.84	0.8795
SVM		0.7969	0.87	0.8813
RF		0.8762	0.91	0.9218

3.2. Probability of Areas with Forest Fire Risk in the Amazonas Region

Figure 5 shows the forest fire risk maps classified into five classes, where it is shown that the areas with very high risk are located in the southern part of the department of Amazonas, and very low risk areas are located in the northern part.

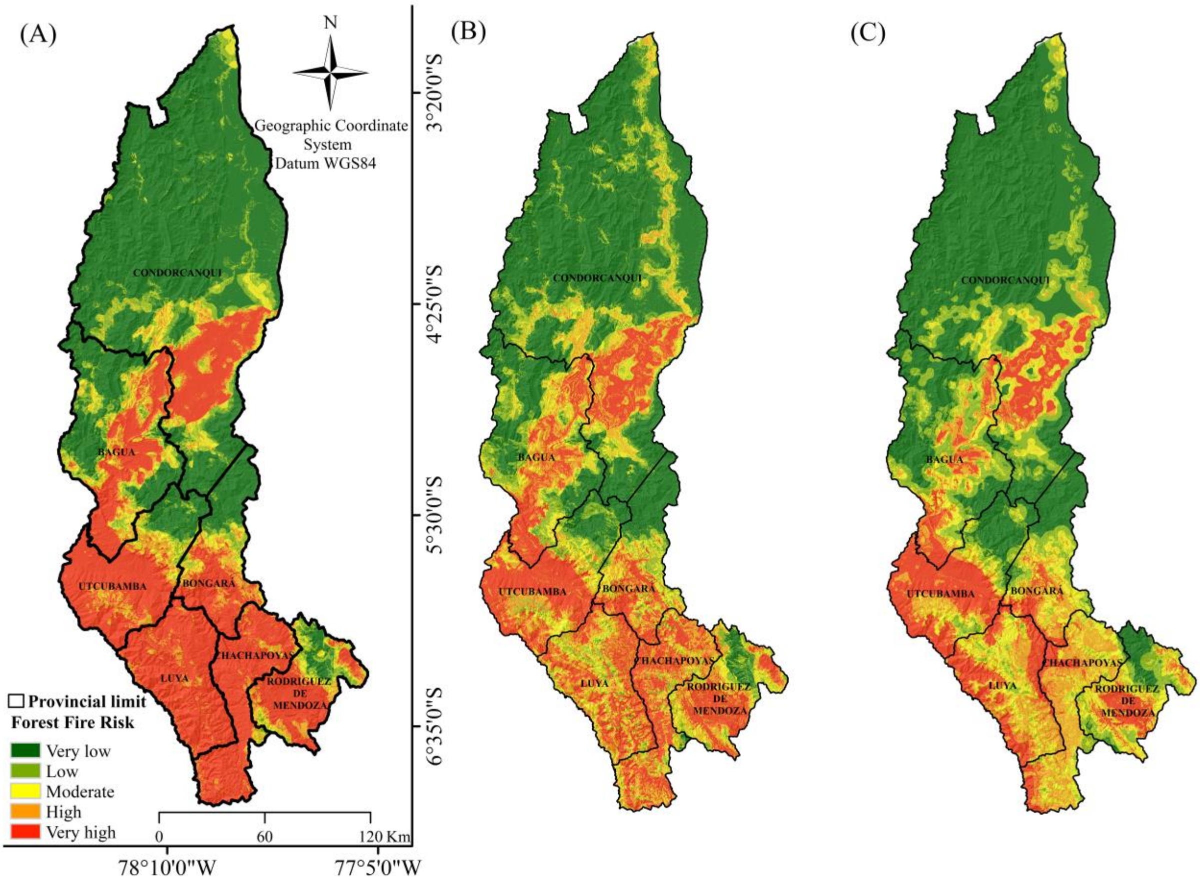

Figure 5. Forest fire risk maps. (**A**) SVM, (**B**) Random Forest, (**C**) MaxEnt.

Table 5 shows that the three machine learning models, RF, SVM, and MaxEnt, have similar values in risk level: very low risk of 39.30%, 40.99%, and 40.71% and very high risk of 21.15%, 37.54%, and 15.61% for the territory with the RF, SVM, and MaxEnt models, respectively (Figure S1). In addition, a mean 24.77% of the territory of the Amazonas department has a very high risk level for the occurrence of forest fires, and 40.33% of the region has a very low risk level.

Table 5. Level of risk per machine learning model assessed in the Amazonasdepartament.

Level of Risk	RF		SVM		MaxEnt		Average	
	ha	%	ha	%	ha	%	ha	%
Very Low	15,441.00	39.30%	16,108.00	40.99%	15,995.00	40.71%	15,848.00	40.33
Low	4977.00	12.67%	3108.00	7.91%	5999.00	15.27%	4694.67	11.95
Moderate	4750.00	12.09%	2304.00	5.86%	5722.00	14.56%	4258.67	10.84
High	5812.00	14.79%	3024.00	7.70%	5442.00	13.85%	4759.33	12.11
Very High	8312.00	21.15%	14,749.00	37.54%	6135.00	15.61%	9732.00	24.77
Total	39,292.00	100.00%	39,293.00	100.00%	39,293.00	100.00%	39,293.00	100.00%

Table 6 presents results for the level of risk in the provinces of the Amazonas departament. It can be seen that with the MaxEnt model, 44.48% of the Utcubamba province has a very high risk level (1927.39 km^2). With the RF model, 47.32% of the province of Chachapoyas has a very high risk level (1554.01 km^2). With the SVM model, the province with the most significant area (3346.92 km^2) with a very high risk level is Luya (93.27% of the total area).

Table 6. Class of forest fire risk areas in the provinces of the Amazonas department.

Model	Province	Very Low	Low	Moderate	High	Very High
		km	km	km	km	km
MaxEnt	Bagua	2100.68	1764.04	815.89	810.63	726.90
	Bongará	963.15	516.67	718.07	536.47	400.82
	Chachapoyas	43.06	283.29	872.70	1524.00	560.74
	Condorcanqui	13,101.72	2606.06	1300.53	579.01	1044.65
	Luya	0.27	163.57	873.27	1202.64	1348.71
	Utcubamba	874.59	480.63	434.39	616.61	1927.39
	Rodriguez de Mendoza	486.49	632.96	791.07	415.90	519.31
Random Forest (RF)	Bagua	1962.17	1111.46	882.32	995.05	1,267.13
	Bongará	1011.98	396.11	537.60	500.74	688.75
	Chachapoyas	31.03	185.63	473.05	1040.07	1554.01
	Condorcanqui	12,172.85	2476.89	1541.22	1137.76	1303.25
	Luya	10.81	252.77	659.77	1113.16	1551.95
	Utcubamba	664.00	493.69	506.28	758.48	1911.17
	Rodriguez de Mendoza	260.48	371.37	586.50	685.59	941.79
Support Vector Machine (SVM)	Bagua	2255.49	743.23	664.24	719.21	1835.96
	Bongará	970.95	208.27	277.41	498.49	1180.06
	Chachapoyas	3.87	26.17	81.06	350.70	2821.98
	Condorcanqui	13,649.94	1745.92	932.01	551.50	1752.60
	Luya	-	-	2.66	238.88	3346.92
	Utcubamba	733.77	183.19	258.68	556.11	2601.88
	Rodriguez de Mendoza	291.64	378.19	327.29	473.32	1375.28

4. Discussion

We used hot spots from the MODIS sensor of active fires. The use of these data did not generate any significant error for the modeling; however, the use of the products has some limitations in studies of forest fires due to the low spatial resolution [129,130]. Another limitation leading to error is the spectral bands at 4 µm used for fire detection, which may contribute to the omission of fires [131,132]. Although this sensor has limitations, it has been used for modeling of forest fire risk in studies achieving optimal results, [55,133,134], which is significant and corroborates the reliability of our results. The resolution of the MODIS data can be improved by integrating SAR and optical data [135–137]. To improve the resolution of MODIS data, techniques such as the fusion of higher resolution satellite imagery, such as MODIS fusion with Landsat, can be used [138] with Sentinel 3 [139] and others.

The performance of algorithms depends on the naturalness of the data used, the selection of features, the optimization of parameters, and the use of means such as subjectivity lexicons [140]. In this study, each hyperparameter was optimized by looking for the best performance of each algorithm, taking into account the statistical evaluation parameters (Table 3). In that sense, the random forest model had superior performance against MaxEnt and SVM because it has high classification accuracy, is a robust and flexible algorithm that has better performance to work with complex data, and a large size when the data are unbalanced [108,141].

It was found that the most accurate model was the RF (AUC = 0.91) in comparison with the MaxEnt (AUC = 0.87) and SVM (AUC = 0.84). Therefore, the RF algorithm is proposed as the most optimal algorithm for wildfire risk modeling. Other studies report similar results, highlighting the efficiency of RF for forest fire mapping. Noroozi et al. [138] concluded that the RF model performs better than the Bayesian models, and Gao et al. [139] mentioned that the RF model has higher accuracy for mapping forest fire areas. In the same way, Garg et al. [140] determined that RF has higher accuracy in predicting forest fires than other models.

On the other hand, in the results of the mapping of areas at risk of forest fire occurrence, it was observed that the RF model presented results that more closely resembled reality, while the opposite occurred with the results of MaxEnt and SVM, which had an overprediction in areas of very high risk. This better performance is due to the fact that the RF algorithm has several advantages over other machine learning methods, as it can handle noisy or missing data and categorical or continuous features, does not require assumptions about the distribution of explanatory variables, and can deal with interactions and non-linearities between efficient factors [69]. On the other hand, MaxEnt had a small differentiation in zones, which is uninformative and does not allow its use in practice [28]. SVM has the limitation that it does not work well when the training set is large, as the storage and computational requirements increase with increasing training vectors [142].

The differences in the maps presented (Figure 5) are due to the performance of each algorithm in the modeling of areas at risk of forest fires. Although it is true that all the models presented good statistical metrics, visually, the SVM and MaxEnt models did not offer good visual results, since SVM in the northern part of Amazonas mixed the pixels and generated a result with too much 'noise', while MaxEnt delivered results by way of interpolation only in places where there were more fire points. On the other hand, Random Forest presented more uniform and reliable visual results, as it presented results with less noise and showed classification that was more reliable.

The ML models tested all had excellent statistical performances, with AUC ranging from 0.84 to 0.91, Accuracy higher than 0.95, Recall higher than 0.87, and F1 scores higher than 0.90. Random Forest was the one that presented the best performance in all statistical performance metrics (Accuracy, Recall, F1 score, and AUC). Taking into account these results, it can be stated that the models are feasible for use in predictions since they presented F1 scores higher than 0.7 [115]. This led to the determination that the RF model is better for modeling wildfire risk areas, as these statistical metrics indicate success in classifying areas at risk of wildfire [143,144]. These results are similar to those of other studies that identified RF as performing better statistically than other machine learning models such as SVM [145,146] and K-nearest neighbors (KNN) [147], determining the superiority of the RF model and validating its practical applicability in studies similar to the one presented in this research.

As mentioned above, Random Forest performed best for modeling areas at risk of forest fire occurrence. This superiority is due to the fact that when there are large amounts of RF data, it solves problems of spatial autocorrelation [148], unlike the MaxEnt model, that suffers from over-fitting, which limits the development of a generalized model with independent data due to its weak regularization mechanisms [149]. On the other hand, SVM had low performance mainly because it is an algorithm that needs large amounts of data to perform better, and the accuracy of this model will depend on the configuration it is given [42].

In Serbia, Petrić et al. [146] indicated that distant locations are prone to larger but less frequent forest fires. These reports are similar to the one by Milanović et al. [147], who found that the areas with the highest probability of forest fire occurrence were located in the southeastern part of the study area in all models used in their study. Shao et al. [148] identified areas of high forest fire risk that were mainly concentrated in the northeastern, southwestern, and southern areas of China. Based on these results and the findings of this study, we confirmed that forest fires in Peru are caused by anthropic activities [150] such as the burning of vegetation for migratory agriculture and ancestral practices such as those used to call for rain, selective deforestation, and changes in the use of land cover, which are variables that influence their forest fire risk. In view of this, it is suggested that a focus be placed on the provision of equipment and formation of trained forest fire brigades, as well as the location of control towers and water reservoirs, in areas with very high risk levels [151,152].

Forest fires are determined by climatic characteristics and meteorological events [153,154]. Due to the significant climatic changes that our planet is facing, alterations in the occurrence of forest fires are very likely, and the forest fire rate will increase due to natural variability in the mid-21st century, with fire danger being three times more likely in the summer, when the temperature anomaly exceeds +2 °C [155,156].

Among the provinces of the Amazonas region, the MaxEnt and RF models agreed that the province with the most significant area at very high risk is Utcubamba, with 1927.39 km^2 and 1911.17 km^2, respectively. These results are consistent with the study by Castillo et al. [150], who identified Utcubamba as the province with the highest risk of occurrence of forest fires. The frequency of fire in this province is based on the fact that most of its area consists of seasonally dry forests and has an arid climate, high temperatures, and low rainfall [152]. All of these characteristics of Utcubamba province create a favorable environment for the occurrence of forest fires [154]. On the other hand, Luya, Rodriguez de Mendoza, and Chachapoyas have smaller areas with a very high risk for fire occurrence. This is because, although the number of registered fires is lower in these provinces, they are of great magnitude [15].

5. Conclusions

- This research provides information on forest fire risk areas in the Amazonas department, integrating MODIS data from the 2010–2022 period, geographic information system, and three machine learning models. The results indicate that the RF model showed significant accuracy compared to the other two, achieving an AUC of 0.91. The RF model determined that 21.8% of the Amazonas department has a very high risk of forest fire occurrence.
- The use of forest fire risk maps will allow decision-makers to plan activities such as the training of fire brigades, training of villagers in forest fire prevention, and potential installation of water reservoirs as a preventive measure in areas classified as very high fire risk.

- This research shows that the use of artificial intelligence is a promising technique to detect fire risk early and inform public policies in forest fire prevention. These results could be used for future research in neighboring departments or regions with similar characteristics. Based on the results obtained, we determined that the Random Forest model has great performance in spatial modeling that integrates different variable types and large amounts of data.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/f16020273/s1, Figure S1: Areas of very high risk level for each developed model. (A) SVM, (B) RF, (C) MaxEnt.

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